International Journal of Engineering Education Vol. 35, No. 4, pp. 1008–1017, 2019
Printed in Great Britain
0949-149X/91 $3.00+0.00

The Impact of Procrastination on Engineering Students' Academic Performance*

JI-EUN KIM
Department of Industrial and Systems Engineering, University of Washington, Box 352650, Seattle, WA 98195, USA.
E-mail: jikim@uw.edu

DAVID A. NEMBHARD
School of Mechanical, Industrial and Manufacturing Engineering, Oregon State University, Corvallis, OR 97330, USA.
E-mail: David.Nembhard@oregonstate.edu

The goal of this study is to model the relationships among four variables—*early activity, time-pressure reactivity, underlying performance, and class performance*. The specific research questions are: *Does procrastination mediate the relationship between earliness and academic performance? Do gender differences affect procrastination and academic performance?* This study identifies a set of relationships among four variables using structural equation models. Each variable in the model is rooted in objective measurements through course website datasets and parametric empirical Bayes estimation obtained from 59 undergraduate engineering students. We found that the degree of procrastination, termed time-pressure reactivity in this model, mediates the relationship between early activity and academic performance. We also found significant gender differences among the four variables: female students showed earlier activity and less procrastination, as well as greater academic performance, than male students. In practice, our findings suggest that the measurement of students' time logged on to access course website material can help researchers to estimate students' short-term and long-term academic performance, as mediated through the individualized degree of procrastination.

Keywords: academic performance; time pressure; structural equation approach; gender difference

1. Introduction

Students and non-students alike often deal with procrastination and the need to calibrate levels of effort in relation to time pressures. Procrastination may be defined as a "voluntarily delay of an intended course of action despite expecting to be worse off for the delay" [1, p. 66]. This phenomenon can be found in diverse task domains ranging from daily tasks and decision-making to academic tasks. In the field of education, procrastination has garnered significant interest among researchers, as it has been shown to be one of the strongest predictors of professional and academic struggle and success [2, 3]. Academic procrastination refers to postponing the initiation or completion of tasks such as preparing for exams or completing homework assignments until the last minute [4–6].

To investigate academic procrastination and its effects on performance, many researchers have relied on self-report questionnaires. For example, the Academic Procrastination State Inventory (APSI) has several lists of questions addressing academic-related procrastination behaviors [7]. The Procrastination Assessment Scale-Students (PASS) measures respondents' academic activities, such as writing term papers, preparing for exams or reading assignments, and attending meetings using a 5-point Likert scale [5]. Using these self-report questionnaires, researchers have investigated the relationships between academic procrastination and performance [8, 9]. Although the reliability and validity of the self-report questionnaires have been tested over several decades [10], it is necessary to consider additional methodologies to quantify the behavior of procrastination based on quantitative observation.

A few researchers have observed and recorded college students' online activities and modeled their behavior related to procrastination. The mathematical model in Equation (1) describes human behavior under a deadline [11]. The model follows an exponential distribution, and it shows that the amount of work individuals complete before a deadline increases exponentially as the deadline approaches. In Equation (1), k represents the slope of the exponential curve, and it indicates individual differences in the degree of procrastination, called time-pressure reactivity. The greater an individual's k value, the more the individual procrastinates under a deadline. A denotes the undiscounted work amount, representing the upper bound of the exponential curve.

$$f(x;k) = Ae^{-kx} \quad (1)$$

Despite developments in this area, it should be noted that there is a limited body of research

* Accepted 12 March 2019.

available for modeling procrastination and its impact on academic performance. Using mathematical estimation from observed behavioral datasets, we note that previous studies have relied on self-report questionnaires to measure academic procrastination and its relation to academic performance, which naturally introduces biases such as participants reporting the values they would like to have rather than the values they actually do have. Bivariate correlations examining a single relationship between two variables have also been commonly used. This approach is limited in its practical applications, however, as several factors naturally influence dependent variables. Thus, the goal of this study is to model the effect of procrastination on academic performance using quantitative models. The study identifies a set of relationships among several variables using structural equation modeling. Each variable in the model is rooted in objective measurements developed through course website datasets and parametric empirical Bayes (PEB) estimation.

2. Literature review

To investigate the relationships among academic *activity*, *procrastination*, and *performance*, we outlined prior research that links each of these conceptual measures. We reviewed findings regarding the relationships between procrastination and academic performance, the latter of which includes both short-term and long-term performance. In addition, in order to enhance the quality of our estimations of procrastination, we developed our conceptual model from the relationship between the observable behavior, termed *earliness* below, to estimate procrastination.

2.1 The effects of earliness on academic performance and procrastination

One directly measurable learning activity linked to procrastination and academic performance is observing the *earliness* of learners' activity before a deadline. Recent computer–online learning systems have enabled researchers to track students' earliness behaviors in a more objective way. Academic earliness is known to positively affect academic performance. Auvinen et al. [12] measured engineering undergraduate students online learning activity and quantified earliness as the "*average distance of submissions to deadline*" (p. 267). In their study, students who showed higher values on earliness performed better on class exercises than those who had low values on earliness within this online learning environment that provided relevant performance feedback. Scott and Stone [13] similarly defined earliness as *"the average number of days before the deadline that the last problem in each set was completed"* (p. 465) and found a positive correlation between earliness and exam scores in online learning systems.

Such earliness behavior has also been shown to have correlations with procrastination, as measured by self-report questionnaires. Duffy et al. [14] measured participants' arrival time to meetings and found that participants who reported that they are less likely to procrastinate arrived earlier to meetings. We note that procrastination has been measured by self-report questionnaires in previous studies [3, 15–17], and the result of Duffy et al.'s study is meaningful in that self-report scores and earliness behavior is shown to be correlated [14]. From this, we can infer that early activity can be a negative predictor of procrastination, meaning that the earlier individuals act, the less they procrastinate.

2.2 Procrastination and academic performance

Researchers have also investigated the relationship between procrastination and performance. Much of the literature has demonstrated that procrastination is related to lower academic performance [1, 8, 9, 18–23]. Academic achievement, as indicated by course grades or grade-point averages (GPAs), has similarly been shown to be negatively correlated with procrastination. Researchers have measured college students' procrastination in diverse domains including mathematics [24], writing, and reading [25] using self-report questionnaires. They have found negative correlations between procrastination and GPA. The less students procrastinate, the greater the academic performance they can achieve.

Some researchers, however, have questioned whether delays in work proximate to deadlines always result in negative outcomes. In some studies, procrastination showed no relationship with academic performance [26–28], while in other studies, procrastinators sometimes showed higher academic performance than non-procrastinators [29]. Such contradictory outcomes of academic performance as influenced by procrastination may be due to the different types of procrastination; Researchers have discerned a difference between most procrastinators and *intentional procrastinators* [1, 30]. Most procrastinators hope to change their delaying behaviors, whereas intentional procrastinators, alternately called active procrastinators, deliberately suspend their pacing so that they can work under time pressure in order to increase their motivation. The GPAs of intentional procrastinators tend to be higher than those of passive procrastinators, who inevitably postpone work despite their intentions to spread their work evenly [30]. This mixed relationship between procrastination and academic performance needs to be examined based on quantifiable, refined measurements and reliable modeling.

In assessing academic performance, both long-term (e.g., GPAs) and short-term (e.g., course grades) measurements have been considered [23]. The two measures need to be considered separately because, by definition, procrastination is caused by a lack of impulse control, which leads individuals to sacrifice long-term outcomes for the best short-term outcomes [23]. This relationship between long-term and short-term academic performance has been inferred from previous research showing that students' GPAs are positive estimators of class performance, which can be measured from assignments, projects, quizzes, and exams [31].

2.3 Gender difference in procrastination and academic performance

There are many factors that may affect procrastination, academic performance, and the relationship between the two. One observable factor that affects procrastination and academic performance is gender. Previous investigations of the effect of gender on academic procrastination have found mixed results. One set of studies suggests there are no significant differences in gender when it comes to academic procrastination [29, 32–34]. For example, McKean [35] found the undergraduate-student procrastinators who had high scores on PASS had lower academic GPAs but no significant effect of gender on the relationship between procrastination and GPA was found. Ferrari [36] also could not find any significant effect of gender on procrastination when using Lay's procrastination scale [3]. The other set of studies has found that procrastination differs by gender. Some have reported that male undergraduate students procrastinate more than female students [37–40]. Since researchers have relied on self-report questionnaires to investigate gender differences in academic procrastination, more research using thorough measurements is needed to clarify the effect of gender.

Regarding academic performance in relation to gender, while some researchers have indicated the effect of gender on academic performance differs according to the types of classes in which the students are enrolled [41], researchers mostly have found that female undergraduate students academically outperform male students in diverse domains [42, 43]. For example, in the undergraduate science and engineering major, GPA and class performance have been found to be better for female students than for male students [44]. Female students in medical school have also shown better academic performance and medical training [45].

2.4 Study aims

Given the unsettled questions in the literature regarding the relationships among procrastination, academic performance, and gender, the purpose of this study is to investigate the relationships among earliness, procrastination, and academic performance (long-term and short-term). Also, the current study aims to examine the effect of gender on procrastination and academic performance. To do so, we will employ a structural equation model approach to investigate the relationships among multiple variables at a time and to predict academic performance from students' online behavior, as mediated by the degree of procrastination. The degree of procrastination in this study will be quantified using PEB estimation that produces individual posterior probabilities from both knowledge of the population (prior distribution) and individual-specific probability obtained from observed data (likelihood) [46, 47]. The PEB estimation is especially advantageous when individual sample sizes vary, because it uses pooled information about the state of nature in addition to individual-specific data. The current study is distinguished from previous investigations on procrastination in that it is based on objective measurements of learners' behaviors. That is, we obtained online activity data and then estimated the degree of procrastination using PEB estimation to finally model the relationship between academic performance and procrastination. Given the relationships found in prior research, the specific research questions of the current study are as follows:

Q1: Does procrastination mediate the relationship between earliness and academic performance?
Q2: Do gender differences affect procrastination and academic performance?

3. Methodology

To address our research questions, we collected a data set that measures engineering undergraduate students' activity when using a course management website. Individual students' log-on times, GPAs, and class grades were automatically recorded. Based on the students' log-on times, we modeled individual time-pressure reactivity using PEB estimation. We then employed a structural equation approach to model the relationship among earliness, procrastination, and academic performance. Structural equation modeling enables researchers to construct multiple relationships among variables simultaneously [48, 49]. It is useful for analyzing various interrelated relationships among independent and dependent variables, and also to investigate the mediating effects that explain underlying processes in human behavior [50, 51]. Gender differences were further investigated by comparing variables defined in the current research. The following sections provide detailed information regarding the research methodology and analyses.

3.1 Data collection

Fifty-nine (32 male and 27 female) undergraduate engineering students enrolled in a senior level engineering course at The Pennsylvania State University voluntarily participated in this study [52]. During the course, five assignments were given to students, which evaluated and gave additional practice to students on concepts and their related calculations, in the class. Each assignment consisted of multiple questions, with each question accessed separately in the assignment folder of the course website, which was organized and maintained by a university course management system. This allowed for the tracking of students' activities on individual questions, including estimates of the amount of time spent on each assignment. This in turn allowed for estimating and quantifying student behavior related to when they worked on assignments, for how long, and how much in advance of the deadlines. The questions were made available on the course website eight days ahead of each assignment's due date, and students were asked to upload their completed work to the website. For this study, we collected data from the course website in an automated fashion. These data included the time and frequency of students' log-ons accessing each question for each assignment, the students' class grades, and their GPAs. We adapted the approach taken by König and Kleinmann [11], using page hits and timing of access of the course website to fit the dataset into the exponential curve expressed in Equation (1). All the individual information was coded so that the researchers could not see the students' personal records. We note that it is possible within this approach for individual student behavior to include accessing the assignments very early and submitting them very late, while performing the actual work somewhere in between. We remark that this aspect of work in the contemporary education environment is also a dimension of procrastination, and would be a part of the collected data. The level of individual instrumentation did not allow us to further separate the performance times. That is, we know how far in advance of the deadline students accessed each question, and similarly, how far in advance of the deadline they submitted their answers, and thus are able to estimate the span of time that was spent with each question.

3.2 Definition and measurement of variables

To begin testing this study's structural model, four variables were defined and measured. The four variables were *early activity*, *time-pressure reactivity*, *underlying performance*, and *class performance*, which are summarized in Table 1. *Early activity* refers to the time students dedicate to work prior to a deadline, and it was calculated as the average number of days the students studied prior to the deadline, as determined by when the students accessed each assigned question. For example, if the value of a student's early activity is 3 (days), on average, the student begins studying three days prior to the deadline. This implies that the students with greater values for early activity tended to study further ahead of the deadline than students with smaller values for early activity. The measurement of early activity is indicated by μ, representing the average number of days students worked prior to the deadline, and it was calculated by the summed time-to-deadline calculated in days divided by the number of log-ons (n). The value of n varied for each of the 59 individuals, with an average of *26.36* ($\pm$ 1.41 SD) and a 95% confidence interval of (*23.53, 29.18*). We assumed that the number of log-ons and the timing when students logged on represented their activity. We remark that the frequency and timing of students' log-ons for each question may better represent early activity than their dwelling time, because it is possible that students leave the page open but engage in other activities such as watching movies or playing games.

Time-pressure reactivity refers to the degree of procrastination and is represented by k, as shown in Equation (1) [11]. The k values were obtained from the study's 59 individuals using PEB estimation [52]. We used the PEB rather than frequentist estimation because the former provides informative posterior distributions especially for individuals with relatively small sample sizes based on information from both the data collected and the prior knowledge of a population [47, 53]. Equation (2) expresses the traditional Bayesian approach, using parameter k to represent the unknown state of nature, time-pressure reactivity in this study, and using μ to represent the available data. In the Bayesian approach represented by Equation (2), prior distribution $f(k)$, which conveys the available information prior to having individual-specific data, and likelihood $f(\mu|k)$, which considers the effect of k on the prior distribution, were employed to produce the posterior distribution, $f(k|\mu)$. Specifically, to produce the individual posterior distribution in terms of $k, g(k)$, the *Gamma* (α, β) conjugate prior distribution for k, represented by

$$\frac{\beta^{\alpha} k^{\alpha-1} e^{-\beta k}}{\Gamma(\alpha)},$$

was multiplied by the individual Gamma (*n, k*) distribution, as indicated by

$$\frac{k^{n} \mu^{n-1} e^{-k\mu}}{\Gamma(n)}$$

in Equation (3) [52]. We used the individual Gamma (*n, k*) distribution as the likelihood function because the sampling distribution of individuals' time-pressure reactivity represented by the exponential distribution in Equation (1) is known to follow the Gamma distribution [53, 54].

$$f(k|\mu) = \frac{f(\mu|k) \cdot f(k)}{f(\mu)} \tag{2}$$

$$g(k|\mu) = \frac{\beta^{\alpha} k^{\alpha-1} e^{-\beta k}}{\Gamma(\alpha)} \cdot \frac{k^{n} \mu^{n-1} e^{-k\mu}}{\Gamma(n)} \cdot \frac{1}{g(\mu)} \tag{3}$$

It was shown that an individual's maximum likelihood of the posterior distribution through Bayesian estimation improves the validity of individual time-pressure reactivity as compared to point estimates by showing reduced variances [52].

Underlying performance refers to each student's quantified long-term academic performance, measured by students' GPAs. Finally, *class performance* is defined as short-term academic performance, measured by an individual's overall class grade.

3.3 Structural equation modeling

Fig. 1 illustrates a conceptual model of the relationship among early activity, time-pressure reactivity, underlying performance, and class performance. In this conceptual model, early activity is indicated as a predictor, since (1) the relationship can be inferred from a literature review, as described in the previous section, and (2) early activity can be used to obtain time-pressure reactivity using PEB estimation [52]. Time-pressure reactivity is used to determine whether there are any mediating effects on the relationship between early activity and underlying performance, given previous research showing relationships between procrastination and GPA. Finally, underlying performance, as represented by GPA, is indicated as a predictor of class performance. Through the model shown in Fig. 1, we are able to investigate direct, indirect, and mediating effects among the four variables. The *SEM* package in *R* was used to generate the structural equation model [55].

4. Results

4.1 Descriptive statistics

Table 2 illustrates the descriptive statistics for the four variables—early activity, time-pressure reactivity, underlying performance, and class performance. Early activity, which was calculated by μ, produced an average of 2.302 days, representing that on average, students studied 2.302 days prior to deadlines. Time-pressure reactivity, measured

Table 1. Definition and measurement of variables

Variable	Definition	Measurement
Early Activity	Time students dedicate to studying prior to a deadline	μ
Time-Pressure Reactivity	Degree of procrastination	k
Underlying Performance	Long-term academic performance	GPA
Class Performance	Short-term academic performance	Class Grade

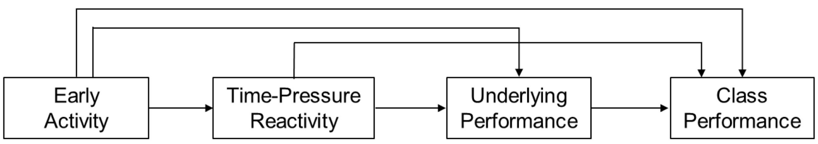

Fig. 1. Conceptual model for predicting class achievement.

Table 2. Descriptive statistics of four individual variables

	Early Activity	Time-Pressure Reactivity	Underlying Performance	Class Performance
Average	2.302	0.781	3.172	85.311
Median	2.272	0.438	3.210	86.140
SE	0.176	0.125	0.060	0.763
95% CI	(1.950, 2.654)	(0.531, 1.031)	(3.053, 3.292)	(83.784, 86.838)

by k, resulted in an average of 0.781, meaning that the slope of exponential distributions implying the degree of procrastination was 0.781. Underlying performance, as determined from students' GPAs, averaged 3.172 on a 4.000 scale. Class performance had an average of 85.311% out of 100% when observing students' activity. Both underlying performance and class performance were taken to represent academic performance in this study.

4.2 Gender differences in earliness, procrastination, and academic performance

We found significant gender differences among the four variables. Fig. 2 illustrates the results of the nonparametric analyses examining early activity, time-pressure reactivity, underlying performance, and class performance. All four variables showed significant differences between male and female students. Early activity was greater for female students (Mann-Whitney; $p = 0.0268$), while time-pressure reactivity was lower for female students (Mann-Whitney; $p = 0.0146$). The female students showed greater underlying performance (Mann-Whitney; $p = 0.0001$) and greater class performance (Mann-Whitney; $p = 0.0123$) than the male students.

4.3 The relationships among earliness, procrastination and academic performance: a structural equation model

To construct a structural equation model, we analyzed the correlations among the four variables for all participants. All four variables—early activity, time-pressure reactivity, underlying performance, and class performance—were initially tested and found to follow normal distributions (Kolmogorov–Smirnov tests: D = 0.084, 0.150, 0.096, 0.101, respectively; $p > 0.1$). The data were then transformed using Z-standardization. Table 3 shows the Pearson's correlation coefficient between each set of two variables. Early activity had a significant negative correlation with time-pressure reactivity but a positive correlation with underlying performance. Time-pressure reactivity showed a significant negative relationship with underlying performance, which had a strong positive correlation with class performance.

Based on prior research and the bivariate correlations found among the variables, the conceptual model in Fig. 1 was tested. Fig. 3 summarizes the significant structural equation model results. Specifically, Fig. 3 shows that early activity negatively predicts time-pressure reactivity ($\gamma = -0.499$, $p < 0.001$), indicating that greater values of early activity are related to lower degrees of procrastination. This implies that the earlier students dedicate time to studying prior to a deadline, the less they procrastinate in their studying. Time-pressure reactivity negatively predicted underlying performance ($\gamma = -0.294$, $p < 0.05$), which subsequently had a positive relationship with class performance ($\gamma = 0.652$, $p < 0.001$). This implies that procrastination behavior predicts low academic performance in

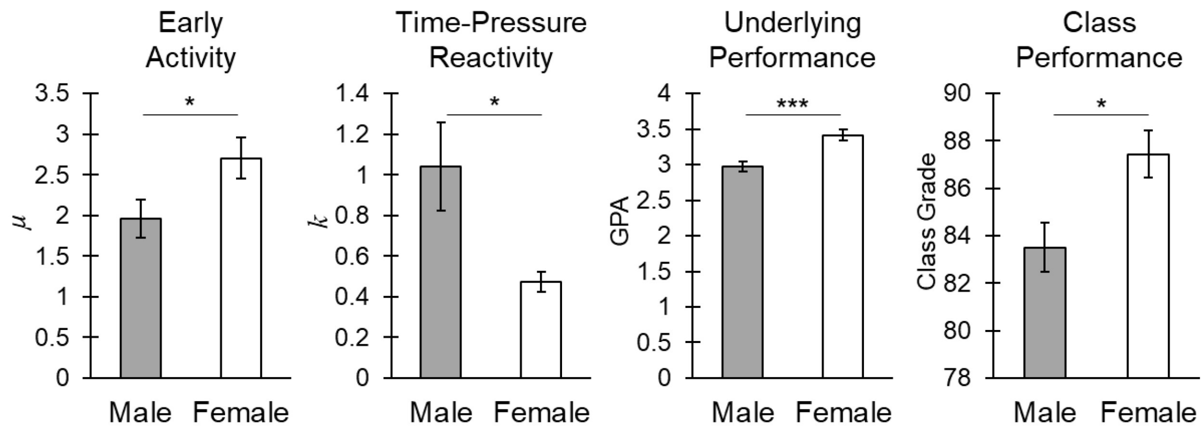

Fig. 2. Gender differences in four variables. $*p < 0.05$, $**p < 0.01$, $***p < 0.001$.

Table 3. Correlation coefficient between each set of two variables

Variable	1	2	3	4
1. Early Activity	–			
2. Time-Pressure Reactivity	–0.499***	–		
3. Underlying Performance	0.297*	–0.294*	–	
4. Class Performance	0.010	–0.109	0.599***	–

$*p < 0.05$, $**p < 0.01$, $***p < 0.001$.

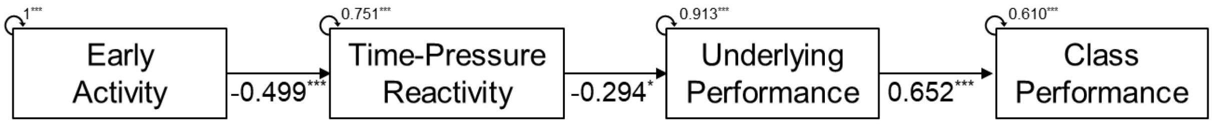

Fig. 3. Mediating effect of time-pressure reactivity on the relationship between early activity and academic performance in a structural equation model. *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$.

both the long term (i.e., GPA) and the short term (i.e., class achievement).

The structural model in Fig. 3 also indicates the mediating effect of time-pressure reactivity on the relationships among early activity, underlying performance, and class performance. Early activity did not show any significant predictive capability for underlying or class performance ($p > 0.05$). Given that time-pressure reactivity mediated early activity and academic performance, but early activity did not predict underlying or class performance, the model had a full mediation of time-pressure reactivity. That is, the effect of early activity on academic performance is indirect [51]. The structural model in Fig. 3 was supported by goodness-of-fit indices: The CFI for this model was 0.980 and the SRMR was 0.058, which are greater than the recommended 0.96 and lower than the recommended 0.09, respectively [56].

We found no differences between male and female students regarding the relationships among variables in the structural equation model. This may be due to the reduced sample size that came from dividing the dataset into the two sub-groups. However, the significant gender differences in the four variables found in Fig. 2 agree with the findings from the structural equation model illustrated in Fig. 3. That is, female students' earlier activity, lower time-pressure reactivity, greater underlying performance, and greater class performance compared to their male counterparts' accord to the relationships among the four variables in the structural equation model. A greater value for early activity predicts lower time-pressure reactivity, mediating greater underlying performance and greater class performance.

5. Discussion

The current study found that the earlier students begin to study prior to a deadline, the less they tend to procrastinate, which ultimately results in higher performance. In addition, significant gender differences were found in the four observed variables. The significant structural equation model in this study indicates that researchers can predict students class performance early-on, by using students' log-on times and activity, called early activity in this study, in the middle of the class through the mediating effect of time-pressure reactivity and GPA. The finding that early activity is a predictor of class performance is in line with previous research findings showing that school engagement is positively correlated with students' academic performance. Wang et al. defined behavioral school engagement as "the actions and practices that students direct toward school and learning" [57, p. 466] and used a five-point scale questionnaire in order to measure behavioral engagement. They found that low scores on school participation were associated with low GPAs. In the current study, early activity was found to have a reciprocal relationship with engagement, as represented by the frequency of log-ons (n). This is because early activity was calculated based on the summed studying time prior to a given deadline shown in days divided by the number of log-ons (n).

Male students' lower academic performance in this activity can be partly explained by procrastination, given that lower values for early activity predict greater levels of procrastination, which subsequently result in weaker academic performance according to the structural equation model. This result of the different values of variables by gender implies that, no matter the reason or direction of gender differences in academic performance, we may need to consider these gender differences when designing class systems.

We note several limitations of the current study. First, we employed a sample of 59 participants from a specific course to fit to our structural equation model. The limited number of participants may be one reason that we found no significant differences in the structural equation model by gender or in the models that include gender as a variable. However, using Iacobucci [58]'s recommendation of a sample size greater than 50, we showed a saturated CFI in the structural equation model. Second, there may be potential bias in measurement based on a course website, although the instrument used was adapted from prior studies [11, 52]. We used the number and timing of log-ons per participant to estimate the participants' activity, but the captured click stream data may not precisely represent their activity for the designated task. For instance, it is possible that students downloaded resources at a particular point in time or logged on to view the assignments and came back only after checking emails or watching television. Future studies might consider implementing more elaborate measurement systems for extracting the time spent on a designated assignments. Third, we used a convenience sample, which was made up of 59 undergraduate engineering students enrolled in the same course who are similar in age (21–26 years old) and have relatively similar levels of academic preparation. Data collected from different settings should be used in future studies to increase the reliability of the current findings.

These results imply that the measurement of students' log-on times in accessing course website material can help researchers to estimate students' short-term and long-term academic performance, as mediated through individualized time-pressure reactivity. The finding that students' class grades and GPAs can be estimated from students' time logged on to a given course website is applicable to online learning systems. Based on students' log-on times, the structural model can generate individualized pacing activity based on individualized time-pressure reactivity, which mediates students' class grades as well as their GPAs. This means that with only students' log-on times and deadlines for various tasks, systems can continually predict and inform students about their proposed pacing patterns and levels of academic achievement. Thus, this model could be applicable to online learning systems in which the interaction between the instructor and students is limited; in particular, it could help students to experience adaptive learning.

The estimation of students' academic procrastination and performance through a model from the current study can be used to provide supportive classroom culture, which affects the number of engineering students retained in the long term. We note that engineering students encounter different challenges from those in other disciplines when it comes to the use of online education [59]. Since mathematical equation manipulation and laboratorial settings are usually required in engineering education, engineering education is known to be the hardest area to teach in online education [60, 61]. Such challenges result in high dropout rates among undergraduate students originally enrolled in schools of engineering. One of the main challenges facing engineering education is retaining students within engineering and in STEM more broadly. Many researchers have addressed concerns regarding the high dropout rates among undergraduate students originally enrolled in the engineering school. Less than 60 percent of undergraduate engineering students reportedly retain their major and very few students switch their major from another field into engineering [62–64]. We note that individual study times and performance can be indicators of persistence and retention in engineering education [63, 65] across gender [66]. The models of earliness, procrastination, and academic performance in this study have implications for student retention and success in engineering education.

6. Conclusions

In answering our two research questions, we found that (1) *the degree of procrastination, (i.e., time-pressure reactivity) was found to mediate the relationship between early activity and academic performance*, and that (2) *gender differences affected earliness, procrastination, and academic performance (i.e., underlying performance and class performance)*. Findings in this study were based on the objective measurement of individual activity gleaned from the course datasets, which is distinctly different from other studies that have relied on self-report questionnaires. The current study collected engineering students' academic activity through a course website, thereby minimizing students' self-report biases. In addition, by using PEB estimation, a more informative estimate of individual time-pressure reactivity was available even with small sample sizes. This means that the structural equation model identified during this study is a reliable tool for estimating individual academic performance rooted in quantified individual time-pressure reactivity. Such findings have implications for student retention and success in engineering education.

References

1. P. Steel, The nature of procrastination: A meta-analytic and theoretical review of quintessential self-regulatory failure, *Psychological Bulletin*, **133**(1), p. 65, 2007.
2. N. Michinov, S. Brunot, O. Le Bohec, J. Juhel and M. Delaval, Procrastination, participation, and performance in online learning environments, *Computers & Education*, **56**(1), pp. 243–252, 2011.
3. C. H. Lay, At last, my research article on procrastination, *Journal of Research in Personality*, **20**(4), pp. 474–495, 1986.
4. E. F. Şirin, Academic procrastination among undergraduates attending school of physical education and sports: Role of general procrastination, academic motivation and academic self-efficacy, *Educational Research and Reviews*, **6**(5), pp. 447–455, 2011.
5. L. J. Solomon and E. D. Rothblum, Academic procrastination: Frequency and cognitive-behavioral correlates, *Journal of Counseling Psychology*, **31**(4), p. 503, 1984.
6. C. A. Wolters, Understanding procrastination from a self-regulated learning perspective, *Journal of Educational Psychology*, **95**(1), p. 179, 2003.
7. H. C. Schouwenburg, Academic procrastination. In *Procrastination and task avoidance*, Springer, Boston, MA. pp. 71–96, 1995.
8. D. Ariely and K. Wertenbroch, Procrastination, deadlines, and performance: Self-control by precommitment, *Psychological Science*, **13**(3), pp. 219–224, 2002.
9. C. J. Perrin, N. Miller, A. T. Haberlin, J. W. Ivy, J. N. Meindl and N. A. Neef, Measuring and reducing college students' procrastination, *Journal of Applied Behavior Analysis*, **44**(3), pp. 463–474, 2011.
10. F. Svartdal, G. Pfuhl, K. Nordby, G. Foschi, K. B. Kling-

sieck, A. Rozental, P. Carlbring, S. Lindblom-Ylänne and K. Rębkowska, On the measurement of procrastination: comparing two scales in six European countries, *Frontiers in Psychology*, **7**, p. 1307, 2016.
11. C. J. König and M. Kleinmann, Deadline Rush: A Time Management Phenomenon and Its Mathematical Description Relationships Between Critical Thinking and Attitudes Toward Women's Roles in Society, *The Journal of Psychology*, **139**(1), pp. 33–45, 2005.
12. T. Auvinen, L. Hakulinen and L. Malmi, Increasing students' awareness of their behavior in online learning environments with visualizations and achievement badges. *IEEE Transactions on Learning Technologies*, **8**(3), pp. 261–273, 2015.
13. N. Scott and B. J. Stone, Student behaviour near a deadline as a predictor of academic success. *Proceedings of the twelfth annual conference of the Australian Society for Computers in Learning in Tertiary Education (ASCILITE)*, pp. 462–467, December 1995.
14. S. E. Duffy, M. I. Feist and S. McCarthy, Moving through time: The role of personality in three real-life contexts, *Cognitive Science*, **38**(8), pp. 1662–1674, 2014.
15. J. M. Gevers, C. G. Rutte and W. Van Eerde, Meeting deadlines in work groups: Implicit and explicit mechanisms, *Applied Psychology*, **55**(1), pp. 52–72, 2006.
16. H. He, Task pacing behaviours in student teams: An experimental study, *Journal of Learning in Higher Education*, **7**(1), pp. 27–28, 2011.
17. W. Van Eerde, F. Beeftink and C. G. Rutte, Working on something else for a while: Pacing in creative design projects, *Time & Society*, **25**(3), pp. 676–699, 2016.
18. M. Balkis, Academic procrastination, academic life satisfaction and academic achievement: the mediation role of rational beliefs about studying, *Journal of Cognitive & Behavioral Psychotherapies*, **13**(1), 2013.
19. G. Beswick, E. D. Rothblum and L. Mann, Psychological antecedents of student procrastination, *Australian Psychologist*, **23**(2), pp. 207–217, 1988.
20. S. M. Moon and A. J. Illingworth, Exploring the dynamic nature of procrastination: A latent growth curve analysis of academic procrastination, *Personality and Individual Differences*, **38**(2), pp. 297–309, 2005.
21. M. Richardson, C. Abraham and R. Bond, Psychological correlates of university students' academic performance: A systematic review and meta-analysis, *Psychological Bulletin*, **138**(2), p. 353, 2012.
22. A. J. Swart, The impact of stress on student tardiness and subsequent throughput rate of engineering students: A case study, *International Journal of Engineering Education*, **24**(4), p. 794, 2008.
23. W. Van Eerde, A meta-analytically derived nomological network of procrastination, *Personality and Individual Differences*, **35**(6), pp. 1401–1418, 2003.
24. M. K. Akinsola, A. Tella and A. Tella, Correlates of academic procrastination and mathematics achievement of university undergraduate students, *Eurasia Journal of Mathematics, Science & Technology Education*, **3**(4), pp. 363–370, 2007.
25. B. A. Fritzsche, B. R. Young and K. C. Hickson, Individual differences in academic procrastination tendency and writing success, *Personality and Individual Differences*, **35**(7), pp. 1549–1557, 2003.
26. J. N. Choi and S. V. Moran, Why not procrastinate? Development and validation of a new active procrastination scale, *The Journal of Social Psychology*, **149**(2), pp. 195–212, 2009.
27. A. J. Howell and D. C. Watson, Procrastination: Associations with achievement goal orientation and learning strategies, *Personality and Individual Differences*, **43**(1), pp. 167–178, 2007.
28. E. H. Seo, The relationships among procrastination, flow, and academic achievement. *Social Behavior and Personality: an International Journal*, **39**(2), pp. 209–217, 2011.
29. T. M. Brinthaupt and C. M. Chin, The relationship of academic cramming to flow experience, 2001.
30. A. H. Chun Chu and J. N. Choi, Rethinking procrastination: Positive effects of "active" procrastination behavior on attitudes and performance, *The Journal of Social Psychology*, **145**(3), pp. 245–264, 2005.
31. S. Devadoss and J. Foltz, Evaluation of factors influencing student class attendance and performance, *American Journal of Agricultural Economics*, **78**(3), pp. 499–507, 1996.
32. J. R. Ferrari, Procrastination as self-regulation failure of performance: effects of cognitive load, self-awareness, and time limits on "working best under pressure", *European Journal of Personality*, **15**(5), pp. 391–406, 2001.
33. L. A. Haycock, P. McCarthy and C. L. Skay, Procrastination in college students: The role of self-efficacy and anxiety, *Journal of Counseling & Development*, **76**(3), pp. 317–324, 1998.
34. M. M. Kachgal, L. S. Hansen and K. J. Nutter, Academic procrastination prevention/intervention: Strategies and recommendations, *Journal of Developmental Education*, **25**(1), p.14, 2001.
35. K. J. McKean, Using multiple risk factors to assess the behavioral, cognitive, and affective effects of learned helplessness, *The Journal of Psychology*, **128**(2), pp. 177–183, 1994.
36. J. R. Ferrari, Procrastinators and perfect behavior: An exploratory factor analysis of self-presentation, self-awareness, and self-handicapping components, *Journal of Research in Personality*, **26**(1), pp. 75–84, 1992.
37. M. J. Khan, H. Arif, S. S. Noor and S. Muneer, Academic procrastination among male and female university and college students, *FWU Journal of Social Sciences*, **8**(2), p. 65, 2014.
38. B. U. Özer, A. Demir and J. R. Ferrari, Exploring academic procrastination among Turkish students: Possible gender differences in prevalence and reasons, *The Journal of Social Psychology*, **149**(2), pp. 241–257, 2009.
39. A. Pala, M. Akyıldız and C. Bağcı, Academic procrastination behaviour of pre-service teachers' of Celal Bayar University, *Procedia—Social and Behavioral Sciences*, **29**, pp. 1418–1425, 2011.
40. C. Senecal, R. Koestner and R. J. Vallerand, Self-regulation and academic procrastination, *The Journal of Social Psychology*, **135**(5), pp. 607–619, 1995.
41. O. O. Demirbas and H. Demirkan, Learning styles of design students and the relationship of academic performance and gender in design education, *Learning and Instruction*, **17**(3), pp. 345–359, 2007.
42. M. Sheard, Hardiness commitment, gender, and age differentiate university academic performance, *British Journal of Educational Psychology*, **79**(1), pp. 189–204, 2009.
43. R. Woodfield, D. Jessop and L. McMillan, Gender differences in undergraduate attendance rates, *Studies in Higher Education*, **31**(1), pp. 1–22, 2006.
44. G. Sonnert and M. F. Fox, Women, men, and academic performance in science and engineering: The gender difference in undergraduate grade point averages, *The Journal of Higher Education*, **83**(1), pp. 73–101, 2012.
45. E. Ferguson, D. James and L. Madeley, Factors associated with success in medical school: systematic review of the literature, *BMJ*, **324**(7343), pp. 952–957, 2002.
46. A. M. Ellison, An introduction to Bayesian inference for ecological research and environmental decision-making, *Ecological Applications*, **6**(4), pp. 1036–1046, 1996.
47. D. S. Wilks, *Statistical methods in the atmospheric sciences* (Vol. 100). Academic Press, 2011.
48. R. B. Kline, *Principles and practice of structural equation modeling*, Guilford Publications, 2015.
49. S. Vinodh and D. Joy, Structural equation modelling of lean manufacturing practices. *International Journal of Production Research*, **50**(6), pp. 1598–1607, 2012.
50. D. P. MacKinnon, A. J. Fairchild, and M. S. Fritz, Mediation analysis. *Annu. Rev. Psychol.*, **58**, pp. 593–614, 2007.
51. D. D. Rucker, K. J. Preacher, Z. L. Tormala and R. E. Petty, Mediation analysis in social psychology: Current practices and new recommendations. *Social and Personality Psychology Compass*, **5**(6), pp. 359–371, 2011.
52. J. E. Kim and D. A. Nembhard, Parametric empirical Bayes estimation of individual time-pressure reactivity, *Interna-*

tional Journal of Production Research, **56**(7), pp. 2452–2463, 2018.
53. A. Gelman, H. S. Stern, J. B. Carlin, D. B. Dunson, A. Vehtari and D. B. Rubin, *Bayesian data analysis*, Chapman and Hall/CRC, 2013.
54. G. M. El-Sayyad, Information and sampling from the exponential distribution, *Technometrics*, **11**(1), pp. 41–45, 1969.
55. Y. Rosseel, Lavaan: An R package for structural equation modeling and more. Version 0.5–12 (BETA), *Journal of Statistical Software*, **48**(2), pp. 1–36, 2012.
56. D. Hooper, J. Coughlan and M. Mullen, Structural equation modelling: Guidelines for determining model fit, *Articles*, p. 2, 2008.
57. M. T. Wang, J. B. Willett and J. S. Eccles, The assessment of school engagement: Examining dimensionality and measurement invariance by gender and race/ethnicity, *Journal of School Psychology*, **49**(4), pp. 465–480, 2011.
58. D. Iacobucci, Structural equations modeling: Fit indices, sample size, and advanced topics, *Journal of Consumer Psychology*, **20**(1), pp. 90–98, 2010.
59. J. Bourne, D. Harris and F. Mayadas, Online engineering education: Learning anywhere, anytime, *Journal of Engineering Education*, **94**(1), pp. 131–146, 2005.
60. G. Al-Hudhud, Intelligent system design requirements for personalizing e-learning systems: applications of AI to education, *International Journal of Engineering Education*, **28**(6), p. 1353, 2012.
61. O. Borras-Gene, M. Martinez-Nunez and Á. Fidalgo-Blanco, New challenges for the motivation and learning in engineering education using gamification in MOOC, *International Journal of Engineering Education*, **32**(1), pp. 501–512, 2016.
62. B. F. French, J. C. Immekus and W. C. Oakes, An examination of indicators of engineering students' success and persistence, *Journal of Engineering Education*, **94**(4), pp. 419–425, 2005.
63. M. Meyer and S. Marx, Engineering dropouts: A qualitative examination of why undergraduates leave engineering, *Journal of Engineering Education*, **103**(4), pp. 525–548, 2014.
64. M. W. Ohland, S. D. Sheppard, G. Lichtenstein, O. Eris, D. Chachra and R. A. Layton, Persistence, engagement, and migration in engineering programs, *Journal of Engineering Education*, **97**(3), pp. 259–278, 2008.
65. R. M. Marra, K. A. Rodgers, D. Shen and B. Bogue, Leaving engineering: A multi-year single institution study, *Journal of Engineering Education*, **101**(1), pp. 6–27, 2012.
66. W. C. Mau, Factors that influence persistence in science and engineering career aspirations, *The Career Development Quarterly*, **51**(3), pp. 234–243, 2003.

Ji-Eun Kim is an assistant professor in the Industrial and Systems Engineering Department at the University of Washington, Seattle. She holds a PhD degree in Industrial Engineering from the Pennsylvania State University and a M.S. degree in Cognitive Psychology from Korea University. Her primary research focuses on measuring, modeling, and designing human performance considering individual differences by employing statistical, physiological, and psychological measurements.

David A. Nembhard is a professor in the School of Mechanical, Industrial, and Manufacturing Engineering and director of the Human Analytics Laboratory at Oregon State University. He holds a PhD degree in Industrial and Operations Engineering from the University of Michigan. His research in industrial engineering focuses on topics including workforce engineering, staffing, scheduling, learning and forgetting, workforce cross-training, human performance in complex systems, and transportation of hazardous materials.